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From innovation to exporting or vice versa? Causal link between innovation activity and exporting in Slovenian microdata

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Abstract

Firm productivity and export decision are closely related to its innovation activity. Product innovation may play a more important role in the decision to start exporting, while the decision for process innovation may be triggered by successful exporting. This suggests that the causality between innovation and exporting may run from product innovation to exporting and conesequently from exporting to process innovation and reverse productivity improvements. Using detailed microdata, including innovation survey, industrial production survey and information on trade, for Slovenian firms in 1996-2002 we investigate this dual causal relationship between firms' innovation and exporting activity. We find no evidence for the hypothesis that either product or process innovations increase the probability of becoming a first time exporter, but find consistent support both in the innovation survey as well as in the industrial production survey that exporting does lead to productivity improvements. These, however, are likely to be related to process rather than product innovations and are limited to a sample of medium and large sized first time exporters only.

JEL classification: D24, F14, F21

Keywords: firm heterogeneity, innovation, exporting, productivity, matching

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1 Introduction

Recent empirical research on exporting behavior of firms has established several empirical regularities. Exporting firms are known to be superior in comparison to non-exporters in terms of productivity, capital intensity, wages and size. Productivity premium of exporting firms received particular attention, with emphasis on testing validity of two pre-eminent hypotheses. The evidence in favor of self-selection of more productive firms into exporting is abundant, while the evidence on reverse causality, namely learning-by-exporting, is rather scarce (see survey of empirical studies by Greenaway and Kneller (2006)).

Large productivity premiums of new exporters (vs. non-exporters) imply that the decision to start exporting is determined by factors that affect productivity of firms before they start exporting. Empirical studies document substantial heterogeneity of productivity of firms within and between industries (Bartelsman and Doms (2000)). However, theoretical models on firm dynamics do not provide a convincing explanation of what generates this firm heterogeneity and divergent evolution of firms, but instead typically assumes productivity that is exogenous to the firm. Models of firm dynamics (Jovanovic (1982), Hopenhayn (1992)) and their extension to international trade (Melitz (2003)) assume that productivity is assigned to a firm by luck of draw from a distribution. After making a draw, there is therefore no way for a firm to change its life path - its survival or death is exogenous to it.

In contrast endogenous growth theory associates productivity of firms to decisions, such as investment into research and development (R&D) and innovation. Romer (1990) argues that technological improvements stem from intentional investment of resources by profit-maximizing firm and that firm's innovative activity is central to its technological progress and productivity growth. Drawing on Vernon's (1966) advances in product lifecycle theory Klepper (1996) demonstrates that product innovation dominates the early stage of the product lifecycle, while process innovation gains relevance in the later stages, after production volumes have increased and efficiency of production becomes increasingly important. Recently, Constantini and Melitz (2007) drew on this by constructing a model which shows that in the anticipation of trade liberalization, a firm may bring forward the decision to innovate in order to "dress up" for the future export market participation.

This reasoning suggests, on one hand, that firm decision to start exporting may be driven by its prior decision to innovate a product and consequently improve its productivity, while on the other hand, firm's exporting activity - due to increased scale of sales - feeds back to its productivity by increased process innovations. Based on this, two causal links can be identified in the relationship between productivity and exporting, both of which are related to firm innovation activity. First, the *product innovation - productivity - decision to export* link may explain how firm decision to invest into R&D and make product innovations drives its productivity and triggers the decision to start exporting. And, second, the *exporting - process innovation - productivity growth* link may provide a missing link in understanding how exporting activity may push a firm to undergo process innovation, which in turn affects its productivity growth.

Over the last decade, many empirical studies, starting with Wagner (1996), have found a positive impact of innovation on exporting. Recently, some studies also find positive impact of process rather than product innovation on productivity growth (for instance Griffith et al (2006; etc.)). Only few studies, however, have attempted to study the whole productivity - exporting link as a causal relationship by controlling for firm innovation activity. While Cassiman and Golovko (2007) and Cassiman and Martinez-Ros (2007) find support for the *product innovation - productivity - export* causal link in the Spanish data, the second, *exporting - process innovation - productivity growth*, causality has been less succesfully tackled.

In this paper we study both directions of the causal relationship between innovation activity and decision to export. We use Slovenian microdata, which combines accounting, innovation and industrial survey data as well as data on foreign trade flows, for the period 1996-2002. This unique dataset allows us to test the prediction that firm's inclination to innovate increases its probability of becoming an exporter as well as the hypothesis that positive learning effects of exporting will result in additional innovations and boost productivity. Starting with joint estimation of simultaneous equations for decisions to export and innovate, we first establish the cross correlation between innovation activity and exporting. Then we apply propensity-score matching techniques, where we match innovating and non-innovating firms (based on the propensity to innovate) in order to compare their likelihood to start exporting (export equation). In addition, we also match exporters with non-exporters based on their propensity to export and investigate whether the two cohorts differ in terms of their innovative effort (innovation equation). The advantage of our approach, however, is that we explore not only the correlation between innovation and exporting status but also try to identify the direction of causality between the two. We do that by estimating the export and innovation equations to reveal whether the lagged innovation output has an impact on firm decision to start exporting, and whether lagged exporting status has an effect on firms decision to become innovative. We find no empirical support for the hypothesis that either product or process innovations increase the likelihood of becoming an exporter. However, we find support that exporting increases the probability of becoming a process rather than product innovator and that exporting leads to productivity improvements. Both effects, however, are limited to a sample of medium and large first time exporters. These findings therefore suggest that participation in trade may positively affect firm efficiency through process innovations.

The paper is organized as follows. After overview of related research in the next Section, in Section 3 we describe the datasets we use and basic descriptive statistics on exporting and innovation activity of Slovenian firms. Section 4 presents results of the basic bivariate probit and matching regressions of our exporting and innovation equations. Section 5 present results on the tests of causality direction between innovation and exporting and some robustness checks. In the last Section we draw main conclusions.

2 Related research

Firm dynamics has become an increasingly popular research field over the last three decades. Extensive empirical work (see survey by Caves, 1998) has documented significant firm turnover and pioneering theoretical work by Jovanovic (1982) and Hopenhayn (1992) related size of firms in terms of employment and sales to and likelihood of survival to productivity. More recently, Bernard and Jensen (1995, 1999) documented substantial differences between exporting and non-exporting firms, which resulted in a new generation of trade models that in addition to firm heterogeneity in terms of productivity feature also share the key features of firm dynamics. Melitz (2003), Bernard et al (2003) and Melitz and Ottaviano (2005) built models that relate observed heterogeneity in foreign markets participation to heterogeneity in firm productivity and yield prediction that only firms with sufficiently high productivity level start supplying goods to foreign markets.

Consistent cross-country evidence on self-selection into exporting and high persistence of exporting status (Roberts and Tybout (1997), Bernard and Jensen (1999), Greenaway and Kneller (2006), Wagner et al (2007)), however, still leaves us short of a convincing explanation, why some firms are initially “better” and how foreign trade participation feeds back to firms’ productivity. There has to be a causal link between firm’s innovation effort and its overall productivity which triggers the decision to start exporting, while on the other hand there also has to be a causal link from firm’s exporting performance to its further productivity improvements. The problem is that there is still no convincing theory explaining the first part of the causality link (firm innovation - productivity - export), while so far no conclusive evidence has been found for the second part of the causal link (learning-by-exporting).

Regarding the innovation effort - productivity - export link, existing theoretical papers explaining firm dynamics (Jovanovic (1982), Hopenhayn (1992)) and its application to international trade (Melitz (2003)) lack a convincing explanation of what “produces” firm’s pre-trade productivity. They relegate firm’s productivity to a draw from a common distribution and neglect the endogeonous relation between firm’s innate ability to create a product and its ex-post productivity, which enables it to enter a market. A novelty in this respect has been the recent contribution of Bernard et al. (2004) who relate firm performance to its ability to create products. In a related paper Bernard et al. (2006) go a step further by assuming firm productivity in a given product to be a combination of firm-level “ability” and firm-product-level “expertise”. While they still rely on the assumption that both the firm-level “ability” and firm-product-level “expertise” are exogenous, their contribution lies in emphasising the importance of firm’s ability to innovate new products. Constantini and Melitz (2007) is the first example of a model of industry dynamics with endogenous innovation and exporting decisions. They show that anticipation of trade liberalization may bring forward the decision to innovate in order to be ready for the future export market participation.

Investment in product innovation may therefore be the key in explaining firm productivity and its decision to enter a market. While a number of empirical studies find a positive impact of innovation on exporting (Wagner (1996), Wakelin (1997, 1998), Ebling and Janz (1999), Aw et al. (2005), Girma et al. (2007)), the exact link from innovation via higher productivity to the exporting decision has not been uncovered yet. An early paper by Vernon (1966) developes a product life cycle theory where product innovation should have an impact on firm productivity and therefore should be indirectely linked to the decision of a firm to start exporting. Klepper (1996) demonstrates that product innovation dominates the early stage of the product lifecycle, while process innovation becomes important in the later stages after production volumes have increased and efficiency of production becomes increasingly important. Recently, a study by Foster et al. (2006) provides some evidence in favor of this by showing that it is firm specific demand variations rather than technical efficiency which essentially determines firm survival and impacts positively firm productivity. This finding implies that firm’s product innovation related to positive demand shocks may explain a large portion of firm’s superior pre-trade productivity level and its consequent decision to start exporting. A recent study by Cassiman and Golovko (2007) finds that for small Spanish firms when product innovation is controlled for the differences in productivity among exporting and non-exporting firms disappear. In a related paper, Cassiman and Martinez-Ros (2007) using a similar sample of Spanish firms find that engaging in product innovation significantly increases the probability of starting to export. Similarly, Becker and Egger (2007) find that, controlling for the endogeneity of innovation, product innovation plays an important role in increasing the propensity to export of German firms, while no such evidence is found for process innovation. These findings, hence, suggest that the productivity - export causal link may well be explained by a firm’s (product) innovation activity.

Regarding the other part of the causal link (exporting - reverse productivity improvements), most of the studies so far failed to find conclusive evidence in support of the positive impact of exporting on productivity growth. Aw et al. (2005) argue that numerous studies that failed to find evidence of learning-by-exporting may have omitted a potentially important element of the process of productivity change: the investments made by firms to absorb and assimilate knowledge and expertise that may be gained from foreign contacts. In other words, exporting activity may have helped firms to become more innovative in the process which may impact productivity growth in the long run.

Recently, few studies find supporting evidence that innovation contributes significantly to firm's productivity growth. Huergo and Jaumandreu (2004), Harrison et al (2005), Griffith et al. (2006), Parisi et al. (2006), and Hall et al. (2007), Damijan et al. (2008) demonstrate that it is process rather than product innovation that drives firm productivity growth. Process innovations have labor displacement effects and are therefore expected to result in significant productivity growth, while, due to the demand effect, product innovations are likely to cause employment growth, but not significant productivity growth. Salomon and Shaver (2005) find some evidence in favor of learning-by-exporting using data on Spanish manufacturing firms. They find that past exporting status increases propensity of firms to innovate.

The discussion so far has shown pieces of evidence that may be put together into a coherent picture connecting firm innovation decision, productivity improvements, export decision and reverse productivity improvements from exporting. The evidence suggest that the causality may run from firm product innovation to superior productivity and subsequent export decision and, on the other side, from exporting triggering process innovations to productivity improvements.

3 Data description

3.1 Data Source

Our empirical analysis of the relationship between innovative activity and exporting is based on firm-level data from Community Innovation Surveys (CIS1, CIS2, CIS3) and firm accounting data (AJPES) for the period 1996-2002. CIS represent an EU wide effort to assess innovation activity and its effects on firm performance. In Slovenia Community innovation surveys are conducted every even year since 1996 by the Slovenian Statistical office (SORS). The surveys are carried out on a censored sample of manufacturing and non-manufacturing firms with no additional conditions put on actual R&D activity or size of these firms. Most importantly, the data gathered by the innovation surveys include, inter alia, information on product and process innovation of firms in two year periods as well as data on the determinants of innovation (employment and expenditure of research and development, etc.). In order to obtain additional insight into the causes and consequences of innovation, we merged CIS data with firm accounting data from annual financial statements as well as with data on firm exports flows. All value data was deflated using NACE 2-digit industry producer price indices, while the capital stock variable was deflated using the consumer price index.[1]

Table 1 compares the sample of firms chosen for the Community Innovation Surveys

[1] A major share of physical capital in firms balance sheets are physical structures. In the period of our analysis the prices of commercial property had grown in line with consumer price index.

and all firms. The sample of surveyed firms represents roughly 10 percent of the population. Average total factor productivity (TFP) and Kolmogorov-Smirnov stochastic dominance tests show that surveyed firms are more productive than all firms in the economy.[2] In addition, surveyed firms are also larger both in terms of sales and employment as well as more capital intensive than the population average.[3] The sample of firms chosen to participate in the Community Innovation Surveys is therefore not representative of the population of Slovene firms and this has to be taken into consideration in the interpretation of results.

Table 1: Comparison in total factor productivity per employee of sample and population data

	number of firms		difference in TFP means	mean (pop.) > > mean (sam.)		K-S stochastic dominance test	
	sample	population		t-stat.	P-value	D-stat	P-value
pooled	9,148	105,560	−300.561	−13.83	0.000	0.099	0.000
1996	1,743	25,243	−89.165	−1.50	0.068	0.049	0.001
1998	2,219	26,649	−584.078	−7.99	0.000	0.102	0.000
2000	2,601	27,653	−404.945	−8.90	0.000	0.173	0.000
2002	2,585	26,015	−533.742	−8.66	0.000	0.203	0.000

Note: TFP means are calculated from residuals of regression of log of value added on log of labor, log of physical capital and industry dummies.
Source: SORS, AJPES and authors' own calculations.

3.2 Descriptive statistics

Given a small size of domestic market, it is not surprising that roughly 85% of Slovene manufacturing firms export (Damijan and Kostevc. 2006). A large portion of Slovene exports is destined to the highly-competitive EU-15 markets (Damijan et al (2007)) and this increases the scope for benefits from either positive spillovers in the exporting markets or by raising the productivity of exporting firms (learning-by-exporting). Damijan and Kostevc (2006) and de Loecker (2007) analyze Slovenian manufacturing firms and find that productivity exhibits a level shift in the year that firms start exporting. This level shift could be either related to capacity utilization, but also to spillovers and learning effects. The latter could reflect introduction of more efficient technologies or increased investment in R&D, and hence in improved innovation activity of exporters. Alternatively, product innovation could stimulate exports especially when exports into highly competitive marketplaces are considered. The causal link between exporting and innovation may

[2]Total factor productivity is constructed as a residual from the production function where value added is being regressed against labor and capital inputs and industry dummies.
[3]For the sake of brevity we do not show these results.

therefore work in both directions as innovation activity could have effect on the future exporting status and, in turn, exporting may boost firm's innovative activity.

Table 2: Comparison of firm characteristics between exporters and non-exporters and innovators and non-innovators for year 2002

	non-exporters		exporters	
	non-innovators	innovators	non-innovators	innovators
Value added per employee	19,627	19,707	21,257	21,293
Capital per employee	48,156	48,781	68,843	65,998
R&D expenditure per employee	0	2,692	0	1,603
Size (sales)	1,158,203	1,180,575	2,843,517	7,612,973
Size (employment)	18	19,5	28	112
Number of firms	692	96	1181	394

Note: Median values of variables are reported. Value added per employee, physical capital per employee and sales are given in Euros (constant 1994 prices).
Source: SORS, AJPES and authors' own calculations.

The characteristics of firms in the sample with respect to both exporting and innovating status are described in Table 2. In line with existing literature, exporters are more productive, larger and more capital intensive than non-exporters. Differences between innovators and non-innovators are more subtle: the former are only marginally more productive when export status is controlled for. Furthermore, innovators are not found to be substantially more capital intensive[4] and in the case of non-exporters they are similar in size to non-innovators. Expenditure on research and development per employee at first seems to indicate that non-exporting firms invest more in research, but, given the size difference, it is clear that the median exporting innovator invests substantially more in absolute terms. Finally, innovating exporters are found to be far larger than non-exporters or non-innovating exporters both in terms of sales and employment.

Table 3 presents an overview of the joint probabilities of being an exporter (non-exporter) and/or innovator (non-innovator). A firm is classified as innovator if it reported to have made process or product innovations in the period of two years prior survey. The results shown in the top panel of the table reveal that innovating firm is more likely to export by almost 40 percentage points.[5] Thus, innovating activity may be a determinant of exporting status or, at the very least, that innovation and exporting are driven by the same determinants. The bottom panel of Table 3, alternatively, demonstrates that exporters are far more likely to innovate than non-exporters. Depending on the year (and survey) in question exporters are between two and five times more likely to innovate than non-exporting firms. Another striking feature of the data is relatively low share of innovating

[4]Among exporting firms, non-innovators are even found to be more capital intensive than non-innovators.

[5]In year 2002 the probability of being an exporter is somewhat larger at 72,4%.

Table 3: Share of exporters (innovators) depending on innovative activity (exports) by firms

year	innovators share of exporters	non-innovators share of exporters
1996	87,4%	49,9%
1998	79,6%	50,5%
2000	87,0%	54,4%
2002	86,5%	72,4%

year	exporters share of innovators	non-exporters share of innovators
1996	28,1%	5,3%
1998	29,8%	9,9%
2000	26,5%	10,1%
2002	23,4%	11,1%

Source: SORS, AJPES and authors' own calculations.

firms in the total number of firms. The average share of firms that have innovated of those surveyed was only about 20%, compared to 65% of German enterprises or 53% of Austrian firms.[6]

Although the positive link between innovative activity and exporting status appears robust, the direction of the relationship (causality) is not evident from the above statistics. Variables such as firm size, capital intensity and foreign ownership may all be positively correlated with innovative activity and exporting and the correlation between these variables may be spurious.

4 Exploring the link between exporting and innovative activity

The evidence shown so far revealed that heterogeneity in terms of productivity between non-exporters and exporters may be explained with past decisions of firms to innovate. The descriptive statistics confirm conjecture that innovators compared to non-innovators are more likely to be exporters and that exporters compared to non-exporters are two to three times more likely to be innovators. Although we still lack a convincing theory, some pieces of empirical findings, including the above descriptive statistics, point towards hypothesized endogenous link between innovation, productivity and exporting. Future exporters may have taken decisions in the past about investing into R&D and undertaking innovation activities, which served to expand their productivity levels and enabled them to

[6] The average share of innovating firms in manufacturing and services for the 27 EU countries was 42% (Fourth Community Innovation Survey, 2007, http://europa.eu/rapid/pressReleasesAction.do?reference=STAT/07/27&format=HTML&aged=0&language).

become exporters. Cassiman and Golovko (2007) and Cassiman and Martinez-Ros (2007) find for a set of Spanish firms that product innovations are crucial driver of exports of small non-exporting firms. Subsequently exporting may lead to further innovations and enabling further improvements in productivity. Findings of Parisi et al. (2006) and Hall et al. (2007), both using Italian microdata but not discriminating between exporting and non-exporting firms, demonstrate that process innovations lead to significant productivity growth through labor displacements. Hence, the causal link should run from innovation to exporting and back to additional innovation. This causal chain is a subject of exploration, with emphasis on distinction between product and process innovations.

In the remainder of this section we explore the correlation between innovation and exporting while the direction of causality between the two is being studied more thoroughly in the next Section.

4.1 Bivariate probit regressions

4.1.1 Methodology

Let us start the study of links between exporting and innovation by modelling joint decisions using bivariate probit model. Our approach is similar to work by Aw et al. (2005) and Girma et al. (2007), who model joint decisions to export and invest resources in R&D or worker training as proxies for the stock of knowledge. However, our data allows us to use the results of efforts to innovate rather than investment of resources. Namely, our data contain information on the actual outcome of the innovation process (actual product and/or process innovations undertaken) by the firm, which allows us to test whether exporting results in greater likelihood to innovate as well as whether innovation effor fosters exporting.

The empirical model relates probabilities of exporting and innovating in period t to lagged firm characteristics (by two periods):

$$Prob(Exp_t = 1) = f(Exp_{t-2}, Inov_{t-2}, X_{t-2}), \tag{1}$$

$$Prob(Inov_t = 1) = f(Inov_{t-2}, Exp_{t-2}, X_{t-2}). \tag{2}$$

Here Exp_t denotes an indicator variable for export status (assuming value 1 if a firm is exporter and 0 otherwise) and $Inov_t$ is an indicator of innovation[7] (taking on value 1 if a firm has innovated in between the two consecutive innovation surveys and 0 otherwise)

[7] We do not discriminate between product and process innovations here, but deal with this distinction below.

while Exp_{t-2} and $Inov_{t-2}$ are the respective lagged variables. X_{t-2} represents a set of controls that also affect the decisions to export and innovate.

Lagged dummy for innovation is the key variable of interest in equation 1.[8] The corresponding coefficient shows whether innovating firms are more or less likely to be exporters. The inclusion of additional explanatory variables is waranted by the relevant literature on the determinants of exports (Wagner, 2007). We include the lagged exporting status, which is used in related literature to account for the sunk cost of entry into the export markets (Roberts and Tybout, 1997). Among other determinants of exporting status (as suggested in the relevant literature) we also include log of labor productivity (value addded per employee), which captures the possibility that more productive firms self-select into exporting. Size measured by log number of employees appears as a determinant of both innovation as well as exporting status (Love and Roper, 2002; Barrios et al., 2003; Damijan and Kostevc, 2006). Inclusion of capital intensity and investment in R&D (both in logs) is necessary since firms with higher capital to labor ratios and greater investments in R&D are more likely to be able to compete in highly competitive mature markets. Finally, we follow Girma et al (2007) and include proxy for penetration of foreign firms with the share of R&D expenditures of foreign owned firms in total R&D expenditures of the sector.[9] We have also estimated specifications where labor productivity and capital intensity were replaced by total factor productivity per employee, but this does not alter the significance or even the magnitude of the remaining variables of interest.

In equation 2 we follow Aw et al. (2005) and Girma et al (2007) and assume that the determinants of innovation are the same as those included in the determination of exporting. The explanatory variable of particular interest is the lagged export status; the corresponding coefficient should indicate whether exporters are more or less likely to innovate than non-exporters and thus provide a channel for learning-by-exporting.[10] Again, our results are not directly comparable to those of Aw et al. (2005) and Girma et al. (2007), as we use data on actual innovation rather than expenditure that may or may not lead to innovation. A positive coefficient on lagged exporting status would imply that exporting leads to "new knowledge" and not just investment in "new knowledge".

In estimation we allow for correlation between residuals of equation (1) and (2). Given that both export status as well as innovative activity are highly serially correlated and that they appear both as dependent and explanatory variables, the error terms of the two equations are likely to be correlated. The two equations therefore need to be estimated simulatenously, which can be done by estimating bivariate probit model with maximum likelihood estimation techniques.

[8] In line with Barrios et al (2003) and Girma et al. (2007).

[9] Again, replacing this variable with the share of innovation of foreign-owned firms in total sectoral innovation does not substantially alter the main results.

[10] Instead of the direct effects of exporting on productivity growth which were not found in Slovene manufacturing firms (Damijan, Kostevc 2006).

4.1.2 Results

Table 4 summarizes the estimates of equation (1) with export status as a dependent variable. Column (1) shows the estimates for the basic equation with lagged innovation, export status, labor productivity, employment and capital intensity. Lagged innovations increase the likelihood of current export status, although, this relationship is not statistically significant. As expected, lagged export status increases the likelihood of current export status. Also, more productive, larger and more capital intensive firms are more likely to become exporters. The impact of lagged innovation and productivity are not robust to omission of time and industry dummies as well as R&D investment and FDI penetration in industry (columns 2-6), which implies that lagged labor productivity and innovation are weak determinants of export decision. The effect of lagged R&D investment on exporting status is not significant either, which confirms the finding that lagged innovation does not affect current exporting status. Finally, columns 5 and 6 contain estimates for specification that distinguish between product (column 5) and process (column 6) innovations. The coefficients suggest that product innovations might have positive impact, although the coefficient is not statistically different from zero. Process innovations are even negatively related to export status.

Table 5 show the estimates of innovation equation (2).[11] Not surprisingly, lagged innovation increases the likelihood of current innovation, which suggests that becoming an innovator requires significant sunk cost. More importantly, lagged export status has a significant positive impact in all but two specifications (columns 3 and 6). In column 3 are shown results with R&D spending, which suggest that R&D spending may be strongly correlated to export status. Column 6 shows results with dependent variable for process innovations. Lagged productivity also matters for the probability to innovate in most specifications, while the effect of lagged capital intensity is not robust to changes in specification. In line with predictions, the probability to innovate is positively linked with the size of the firms, which indicates the importance of scale in research activity.
The results based on bivariate probit regressions show weak support for self-selection and stronger support for learning-by-exporting. However, estimation procedure includes all firms, those that are already exporting and those that are already innovating. If new exporters and new innovators have different response to lagged innovation and export status, then the results of bivariate probit may not be relevant to all firms. Moreover, since probit model does not compare the effects of similar firms, but instead yields results for all firms, we apply matching techniques in subsequent work.

[11] Note that the summary statistics in Tables 5 and 6 are identical as export and innovation decisions are jointly estimated.

Table 4: **Results of bivariate probit regressions**
Export status

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged innovation	0.129	0.054	0.096	−0.093	0.191	−0.041
	(0.088)	(0.112)	(0.213)	(0.291)	(0.231)	(0.219)
Lagged export status	1.876***	2.281***	2.128***	2.443***	2.421***	2.401***
	(0.072)	(0.104)	(0.156)	(0.242)	(0.241)	(0.236)
Lagged productivity	0.126*	0.145	−0.076	−0.067	−0.108	−0.050
	(0.066)	(0.092)	(0.144)	(0.173)	(0.193)	(0.186)
Lagged employment	0.214***	0.166***	0.321**	0.130*	0.177**	0.145*
	(0.035)	(0.042)	(0.071)	(0.077)	(0.084)	(0.082)
Lagged capital intensity	0.144***	−0.108**	0.067	−0.092*	−0.029	−0.064
	(0.042)	(0.052)	(0.085)	(0.129)	(0.129)	0.134
Lagged R&D Investment			0.004	0.025	0.009	0.026
			(0.025)	(0.030)	(0.024)	0.022
FDI penetration in industry		0.151		0.114	−0.097	−0.079
		0.183		0.303	(0.306)	(0.311)
Industry dummies	*yes*	*no*	*yes*	*no*	*no*	*no*
Time dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
N	3812	1551	1428	602	623	623
Log pseudolikelihood	−2423.9	−1098.7	−918.8	−393.7	−410.3	−446.4
ρ	0.125	0.139	0.118	0.275	0.423	0.197
Prob $\rho = 0$	0.058	0.078	0.092	0.063	0.007	0.132

Note: standard errors robust for clustering at firm level in parentheses.
(1) - (4) Both product and process innovation considered,
(5) only product innovation is considered and (6) only process innovation considered
*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.
Source: SORS and AJPES; authors' calculations.

4.2 Matching approach

In order to investigate the above results further as well as to provide a robustness check, we first match innovating and non-innovating firms according to their probability to innovate and then test for the average treatment effects of lagged innovation status on the propensity to export (exporting equation). We employ the following propensity score specification for the probability to innovate

$$Prob(Inov_t = 1) = f(Inov_{t-2}, X_{t-2}) \tag{3}$$

where, again, $Inov_{t-2}$ represents the lagged innovation status, while X_{t-2} captures all other lagged explanatory variables (productivity, employment, capital intensity, investment in research and development, foreign ownership indicator). Based on the propensity score, we match innovating and non-innovating firms in period $t-2$ and test the effects of innovation on the current (t) exporting status. Second, we also match exporting and

Table 5: **Results of bivariate probit regressions**
Innovation status

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged innovation	1.226***	1.396***	0.631***	0.891***	0.912***	0.463***
	(0.064)	(0.091)	(0.134)	(0.196)	(0.166)	(0.132)
Lagged export status	0.223***	0.332***	−0.053	0.536**	0.478**	0.254
	(0.079)	(0.099)	(0.149)	(0.211)	(0.210)	(0.212)
Lagged productivity	0.167***	0.171**	0.199**	0.072	0.092	0.208*
	(0.062)	(0.080)	(0.098)	(0.135)	(0.134)	(0.120)
Lagged employment	0.224***	0.256***	0.178***	0.130**	0.134**	0.228***
	(0.026)	(0.035)	(0.039)	(0.056)	(0.053)	(0.052)
Lagged capital intensity	0.069*	−0.057	0.124*	0.049	−0.042	0.053
	(0.041)	(0.049)	(0.069)	(0.083)	(0.087)	(0.073)
Lagged R&D Investment			0.077***	0.051***	0.057***	0.049***
			(0.014)	(0.020)	(0.017)	(0.014)
FDI penetration in sector		0.793***		0.708**	0.564***	0.651***
		(0.168)		(0.219)	(0.206)	(0.204)
Sector dummies	*yes*	*no*	*yes*	*no*	*no*	*no*
Time dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
N	3812	1551	1428	602	623	623
Log pseudolikelihood	−2423.9	−1098.7	−918.8	−393.7	−410.3	−446.4
ρ	0.125	0.139	0.118	0.275	0.423	0.197
Prob $\rho = 0$	0.058	0.078	0.092	0.063	0.007	0.132

Note: standard errors robust for clustering at the firm level in parentheses.
(1) - (4) Both product and process innovation considered,
(5) only product innovation is considered and (6) only process innovation considered
*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.
Source: SORS and AJPES; authors' calculations.

non-exporting firms based on the probability to export and then test for the average treatment effects of exporting status on innovative activity. We use the following specification to estimate the probability of being an exporter

$$Prob(Exp_t = 1) = f(Exp_{t-2}, X_{t-2}) \tag{4}$$

Based on the propensity score from the predicted probability to export (4), we use nearest neighbour matching by NACE 2-digit industry to match exporting and non-exporting firms at time $t-2$ and then observe the average treatment effects of lagged exporting status on current (t) innovation activity (innovation equation). Table 6 presents estimates of average treatment effects (ATT) that are pooled across all industries. In this instance different types of matching were done industry-by-industry, but the treatment effects were pooled across all industries so that they can be compared with the estimates presented above. We compare estimates of three different types of matching - nearest neighbour matching, kernel matching and radius matching. As Abadie and Imbens (2006) suggest that bootsrapped standard errors may not be valid in the case of nearest neighbour matching[12], we also present sub-sampling based standard errors for average treatment effects in the case of nearest neighbour matching.

The results in Table 6 confirm high and robust correlation between lagged exporting status and current innovation (innovation equation), while the link between lagged innovative activity and current exporting status (export equation) is not confirmed by any of the types of matching. However, as these results present average treatment effects pooled over all industries, it is intresting to look at results for individual industries. The industry-specific average treatment effects for both the exporting and innovation equation are presented in Table A1 in Appendix.[13] With some notable exceptions, we can see that in majority of industries average treatment effects of the export equation reveal that innovators are more likely to be also exporters,[14] while, similarly, the innovation equation, by and large, confirms that lagged exporting status has a significant impact on innovation.[15]

Table 6: Pooled average treatment effects (across industries) of lagged innovation (export status) on current export status (current innovation)

	export equation			innovation equation		
	ATT	SE^a	obs.^{b}	ATT	SE^a	obs.^{b}
nearest neighbour matching	0.006	0.034	314 (36)	0.288***	0.109	437 (17)
nearest neighbour matching^c	0.006	0.041	314 (36)	0.288***	0.111	437 (17)
kernel matching	0.015	0.026	314 (155)	0.268***	0.111	437 (29)
radius matching (r = 0.2)	0.027	0.056	43 (77)	0.254***	0.080	336 (45)

Notes: ^{a} bootstrapped standard errors (100 repetitions)
^{b} number of treatment observations, number of control observations in parentheses.
^{c} sub-sampling based standard errors (100 draws)
*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.
Source: SORS and AJPES; authors' calculations.

[12] Abadie and Imbens (2006) show that due to the extreme non-smoothness of nearest neighbour matching, the standard conditions for bootstrap are not satisfied, leading the bootsrap variance to diverge from the actual variance. The bootstrapped standard errors underestimate the actual standard errors and this can be corrected with subsampling.

[13] Note that we performed these estimations disaggregated by sectors also separately for product and process innovations, but no substantial differences between both were found.

[14] This result is confirmed in 12 out of the 20 industries tested. Additional 4 industries exhibit positive but not significant average treatment effects, while the remaining 4 are negative and non-significant.

[15] Of the 14 industries tested, 10 exhibit positive and significant average treatment effects, while of the remaining four two are negative and non-significant, one is negative signficant and one positive non-significant.

5 Searching for causality using matching approach

5.1 Methodology and descriptive statistics

The bivariate probit and matching results confirm some positive correlation between firms' exporting and innovation activity, but neither of them can be interpreted as causal. Our primary interest is to explore the causal relationship between exporting and innovation, i.e. is decision to start exporting affected by firms' past innovation activity and does past exporting status increase innovation effort? There has not been much empirical work done on this particular issue so far. The only exception being the research by Cassiman and Martinez-Ros (2007) studying the first part of the causal link - from innovation to exporting. Using probit regression, they show that product innovations increase the likelihood that firms decide to become new exporters for small Spanish firms with less than 200 employees.[16] This effect was not found for large non-exporting firms, while for small firms the effect of product innovation on the decision to start exporting diminishes when process innovations are taken into account. They claim that product innovations may be an important missing link between firm heterogeneity, productivity and the decision to export. In a related study Cassiman and Golovko (2007) explore this link directly and find consistent evidence that product innovation drives productivity. For Slovenia, however, Damijan et al (2008) find some empirical support of positive impact of process innovation on productivity growth, but no significant impact of product innovation.

Table 7: Transitional probabilities conditional on becoming an exporter

	$\text{exp}_t = 1 \vert \text{exp}_{t-2} = 0$			
	0		1	
	$\text{product}_t = 0$	$\text{product}_t = 1$	$\text{product}_t = 0$	$\text{product}_t = 1$
$\text{product}_{t-2} = 0$	8,158	849	421	**16**
	(86.4%)	(9,0%)	(4.5%)	(0.2%)
$\text{product}_{t-2} = 1$	294	532	**13**	**11**
	(34.6%)	(62,6%)	(1.5%)	(1.3%)

	$\text{exp}_t = 1 \vert \text{exp}_{t-2} = 0$			
	0		1	
	$\text{process}_t = 0$	$\text{process}_t = 1$	$\text{process}_t = 0$	$\text{process}_t = 1$
$\text{process}_{t-2} = 0$	8,540	678	429	**16**
	(88.4%)	(7.0%)	(4.4%)	(0.2%)
$\text{process}_{t-2} = 1$	255	360	**11**	**5**
	(40.4%)	(57.0%)	(1.8%)	(0.8%)

Source: SORS and AJPES; authors' calculations.

In this section we study both sides of the causal link between innovation and exporting. On

[16] Their results are robust also to alternative econometric specifications, such as linear probability model or conditional logit model.

one hand we examine whether the switches from non-exporting to exporting are induced by past innovation activity and on the other hand we look whether switches from non-innovation to innovation are induced by past exporting status. These switches can be effectively observed by examining the transition probabilities of firms into different states. Table 7 shows that only 2.8% of firms (1.5%+1.3%) that were product innovators in period $t-2$ switched from non-exporters to exporters in period t. Similarly, only 2.6% of process innovators in $t-2$ became first time exporters in period t. Allowing for simultaneous decision to innovate and to start exporting and hence taking into account also innovators in the present period, only 8.7% and 8.9% of all switchers into exporting can be attributed to product or process innovators, respectively. This speaks of rather low probability of advancing from innovators to exporters.

Table 8: Transitional probabilities conditional on becoming a product or process innovator

	product $\text{inov}_t = 1 \mid \text{product inov}_{t-2} = 0$			
	0		1	
	$\text{exp}_t = 0$	$\text{exp}_t = 1$	$\text{exp}_t = 0$	$\text{exp}_t = 1$
$\text{exp}_{t-2} = 0$	1,458	633	46	**16**
	(67.7%)	(29,4%)	(2,2%)	(0.7%)
$\text{exp}_{t-2} = 1$	276	4,492	**5**	**239**
	(5.5%)	(89,7%)	(0,0%)	(4,8%)

	process $\text{inov}_t = 1 \mid \text{process inov}_{t-2} = 0$			
	0		1	
	$\text{exp}_t = 0$	$\text{exp}_t = 1$	$\text{exp}_t = 0$	$\text{exp}_t = 1$
$\text{exp}_{t-2} = 0$	1,467	633	37	**16**
	(68.1%)	(29.4%)	(1.8%)	(0.7%)
$\text{exp}_{t-2} = 1$	275	4,447	**6**	**284**
	(5.5%)	(88.7%)	(0.1%)	(5.7%)

Source: SORS and AJPES; authors' calculations.

On the other hand, the evidence of transition from exporting to innovation is more convincing. Table 8 shows that 4.8% and 5.8% of past exporters became first time product and process innovators, respectively, in the present period. Moreover, when allowing for simultaneous decision to start exporting and to start innovating, 85% and 89% of first time product and process innovators, respectively, can be attributed to be exporters in the past or in the present period. This indicates that among Slovenian firms the probability of exporting to induce innovations is larger than probability of innovations to induce exporting decisions.

In order to estimate the importance of innovation for the decision to start exporting and importance of exporting for the decision to start innovating, we alter our exporting and innovation equations. The exporting equation now restricts a sample of lagged non-exporting firms:

$$Prob(Exp_t = 1 | Exp_{t-2} = 0) = f(Inov_{t-2}) \quad (5)$$

wheras the innovation equation restricts the attention to lagged non-innovating firms:

$$Prob(Inov_t = 1 | Inov_{t-2} = 0) = f(Exp_{t-2}) \quad (6)$$

We use exporting equation (5) to match innovators with non-innovators in period $t-2$,[17] and then, using the average treatment effects approach, test whether previously non-exporting innovating firms are likelier to become exporters in period t than non-innovating non-exporters. Analogously, we estimate innovation equation (6) and match exporters with non-exporters in period $t-2$, to test whether previously non-innovating exporting firms are likelier to become innovators in period t than non-exporting non-innovators.

5.2 Results

Estimates of the average treatment effects of lagged innovative activity on the change in exporting (exporting equation) and of lagged exporting status on the change in innovation activity (innovation equation) obtained with different matching techniques are presented in Tables 9 and 10. Note that we distinguish between product and process innovations, as this may have important implications for the relationship between exporting and innovation. As demonstrated by Becker and Egger (2007), Cassiman and Golovko (2007) and Cassiman and Martinez-Ros (2007) product innovations are crucial for firm's successful market entry, while process innovations help maintaining its market position given the maintained product characteristics. Product innovations should therefore play greater role in the decision to start exporting, while the decision for process innovation may be triggered by successful exporting.

Table 9 (top panel) reveals that when only product innovations are considered, innovators are not more likely to become exporters than non-innovators (export equation). In only one out of four specifications (radius matching) there is a significant but negative impact of past product innovations on decision to start exporting. On the other hand, we find no evidence that exporting status enchances the probability of a firm to become a product innovator. In the Appendix we present estimates of the average treatment effects of specifications (5) and (6) industry-by-industry and find no support for significant causal relationship between exporting and product innovations.

[17] We continue applying the propensity score specifications (3) and (4) .

Table 9: Pooled average treatment effects of lagged innovation (lagged export status) on the change in export status (innovation)

Product innovation

	$\Pr[Exp_t]$			$\Pr[Inov_t^{prod}]$		
	ATT	SE[a]	obs.[b]	ATT	SE[a]	obs.[b]
nearest neighbour matching	0.015	0.014	265 (172)	−0.014	0.057	437 (33)
nearest neighbour matching[c]	0.015	0.013	265 (172)	−0.014	0.046	437 (33)
kernel matching	−0.022	0.015	265 (722)	−0.020	0.038	437 (45)
radius matching (r = 0.2)	−0.024*	0.013	265 (722)	0.013	0.030	331 (45)

Process innovation

	$\Pr[Exp_t]$			$\Pr[Inov_t^{proc}]$		
	ATT	SE[a]	obs.[b]	ATT	SE[a]	obs.[b]
nearest neighbour matching	−0.001	0.016	245 (168)	0.016*	0.008	437 (33)
nearest neighbour matching[c]	−0.001	0.017	245 (168)	0.016*	0.009	437 (33)
kernel matching	−0.030*	0.020	245 (168)	0.016*	0.010	437 (33)
radius matching (r = 0.2)	−0.032**	0.013	245 (756)	0.046***	0.008	326 (45)

Notes: [a] bootstrapped standard errors (100 repetitions)
[b] number of treatment observations, number of control observations in parentheses
[c] sub-sampling based standard errors (100 draws)
*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.
Source: SORS and AJPES; authors' calculations.

In contrast, the bottom panel of Table 9 provides consistent evidence across all specifications that lagged exporting status has a statistically significant positive impact on the probability of becoming a process innovator. Past exporting status is shown to increase the probability of engaging in process innovation in the future by some 1.6% to 4.6%. Again, exporting equation reveals no or even negative significant effects of lagged process innovation on becoming an exporter.

In Table 10 we provide results disaggregated by size classes for the relationship between exporting and process innovations. Interestingly, we find consistent evidence of causal link from past exporting to future process innovation for the samples of medium and large firms and no significant impact for small firms. Moreover, the marginal effect of exporting on process innovation seems to increase with firm size. While for a group of small firms the effect of exporting on process innovation is low and mostly insignificant, for a group of medium sized firms, exporting is shown to increase the probability of engaging in process innovation by some 4.6% (nearest neighbour matching) to 8.2% (kernel matching). In large firms this effect increases to the range of 5.7% - 6.4%. These findings support a version of the learning-by-exporting hypothesis where exporters use their exporting status to improve their knowledge of the production process, marketing activities and managerial skills that lead to improvements in TFP.

Table 10: Pooled average treatment effects of lagged process innovation (lagged export status) on the change in export status (process innovation) for three size classes

	$\Pr[Exp_t]$			$\Pr[Inov_t]$		
Small ($10 < Emp < 50$)	ATT	SE[a]	obs.[b]	ATT	SE[a]	obs.[b]
nearest neighbour matching	−0.024	0.037	95 (1026)	0.010	0.014	1050 (375)
nearest neighbour matching[c]	−0.024	0.038	95 (1026)	0.010	0.013	1050 (375)
kernel matching	−0.074***	0.020	95 (1389)	0.010	0.015	1050 (375)
radius matching (r = 0.2)	−0.077***	0.019	44 (382)	0.046***	0.008	4340 (766)
Medium ($50 < Emp < 200$)	ATT	SE[a]	obs.[b]	ATT	SE[a]	obs.[b]
nearest neighbour matching	0.027	0.024	270 (1177)	0.046*	0.024	1386 (152)
nearest neighbour matching[c]	0.027	0.021	270 (1177)	0.046	0.032	1386 (152)
kernel matching	0.023	0.022	270 (1351)	0.082*	0.049	1386 (154)
radius matching (r = 0.2)	0.014	0.025	105 (247)			
Large ($200 < Emp$)	ATT	SE[a]	obs.[b]	ATT	SE[a]	obs.[b]
nearest neighbour matching	0.005	0.011	275 (1532)	0.064***	0.023	1603 (164)
nearest neighbour matching[c]	0.005	0.011	275 (1532)	0.064***	0.024	1603 (164)
kernel matching	0.011	0.012	275 (1575)	0.057*	0.029	1603 (164)
radius matching (r = 0.2)	0.011	0.011	93 (88)			

Notes: [a] bootstrapped standard errors (100 repetitions)
[b] number of treatment observations, number of control observations in parentheses
[c] sub-sampling based standard errors (100 draws)
*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.
Source: SORS and AJPES; authors' calculations.

5.3 Robustness check: Industrial production data

5.3.1 Data description and summary statistics

In this subsection we explore whether the above finding of no impact of exporting on product innovations and significant impact of exporting on process innovations (for a sample of medium and large sized firms) is also consistent with other available microdata. The results based on innovation surveys are often questioned as responses of firms may not be entirely consistent with their actual behavior. To check whether and how the above results obtained from innovation surveys are robust to use of alternative measures of product and process innovation, we use data from the industrial production survey (IPS) for the period 1995-2003. This survey asks the respondents to list the products they produce and sell to domestic and foreign markets, allowing us to consider whether firms that start exporting increase the number of products at higher pace than firms that do not decide to serve foreign markets.

The participation in the IP survey in Slovenia is obligatory.[18] The survey sheets are sent

[18] The survey is conducted by the national Statistical Office.

out to a sample of firms that reported to employ at least 20 workers in the preceding year. After being included in the survey, a firm continues to receive survey sheets even if the number of employees declines below the stated limit. Since many firms start exporting before they are first included in the survey, many new exporters are excluded from analysis. As a consequence, the sample of new exporters in the IP survey is reduced to 108 firms out of 776 in the complete dataset. Table 11 compares the key characteristics of all new exporters and new exporters that were in the IPS for the period 1995-2002. The average size of all new exporters is as low as 20 employees, while the average firm size in the censored IP sample is almost four and a half times greater measured with either employment or annual sales. In other words, while the whole sample of firms is over representative of micro and small firms, the firms with less than 20 employees are excluded from the IP sample, leaving in the sample mostly medium sized first time exporters. On the other side, the average productivity and capital intensity of new exporters in the IP survey correspond to 80 and 86 percent of respective values for the entire sample of new exporters. Clearly, inferior labor productivity and capital intensity of censored sample may affect the results on differential performance of new exporters.

The last column of Table 11 shows the key statistics for the sample of surveyed firms that did not export. Comparison of firm characteristics in the last two columns suggests that firms that did not start exporting were on average smaller, slightly more productive and less capital intensive.[19] On average these two sets of firms produced similar number of products.

5.3.2 Impact of exporting on number of products and productivity growth

This section reports the average treatment effects (ATT) on treated firms caused by exporting regarding product and process innovation. Note that in this approach we differently account for both types of innovations as compared to the approach in the previous subsection by observing the effects of exporting on number of firm's products and on firm's total factor productivity (TFP) growth. Here, an increase in a number of products provides a direct evidence of firm's product innovation, while an increase in the TFP provides a direct evidence of firm's process innovations. Note that this distinction is based on findings of Harrison et al (2005), Griffith et al (2006), Parisi et al (2006), and Hall et al (2007) which show that process innovations have labor displacement effects and are therefore expected to result in significant productivity growth, while, due to the demand effect, product innovations may likely cause employment growth and, thus, may not result in significant productivity growth.

[19] Lower productivity of new exporters than non-exporters is specific to our censored sample. Damijan, Kostevc and Polanec (2008) show that productivity of new exporters is higher than the productivity of non-exporters.

Table 11: Firm characteristics of new exporters and non-exporters, 1995-2002

Variable	All new exporters	IP sample of new exporters	IP sample of non-exporters
Number of firms	776	108	238
Employment	19.66	89.78	38.03
	(165.57)	(432.42)	(47.95)
Turnover	194.84	957.51	286.85
	(2060.34)	(5474.22)	(468.28)
Labor productivity	3.03	2.41	2.56
	(2.75)	(1.62)	(1.64)
Capital intensity	4.40	3.89	3.26
	(8.82)	(6.42)	(5.77)
Number of products	-	3.72	3.93
	-	(3.48)	(4.36)

Source: SORS, Slovenian Customs Office and own calculations.
Notes: Table consists of average values for key firm characteristics and standard deviations in parentheses. Monetary variables are given in millions of Slovenian tolars (1994 constant prices).

The propensity scores for export decision is estimated by

$$Prob(Exp_t = 1|Exp_{t-1} = 0) = f(\log TFP_{t-1}, \log k_{t-1}, \log l_{t-1}, \log NoP_{t-1}, time) \qquad (7)$$

where explanatory variables are lagged log of TFP, log of capital intensity k, log of employment l and log of number of products NoP and $time$, which denotes dummy variables for cyclical effects (annual dummies).[20] All regression coefficients with exception of number of products (reported in Table 14 in Appendix) are statistically significant. In particular, size of firms is the most important explanatory variable. Validity of calculated treatment effects is granted by the fact that the observables behind the propensity score are balanced.

Based on the above propensity score, we match first time exporters with non-exporters in period $t-1$ by using either nearest neighbour matching or kernel matching, and then estimate average treatment effects of exporting on treated firms with respect to product and process innovation.

Table 12 reports changes in log of number of products using nearest neighbor and kernel matching for $t+1$, $t+2$ and $t+3$ years after firms start exporting. The results suggest that firms that start exporting increase the number of products faster, however, these effects are marginally significant only one year after start of exporting in case of nearest neighbor matching and two years after start of exporting in case of kernel matching. These results

[20]This propensity score equation requires that firms did not export in period $t-1$. This is different to previous specifications, which we constrained by biannual data on innovation survey.

Table 12: Treatment effects for number of products

Nearest neighbor matching					
Time span	Treated	Controls	ATT	Std.Err.	t-stat
t+1/t	165	118	0.083*	0.044	1.872
t+2/t	165	108	0.067	0.051	1.303
t+3/t	165	98	0.051	0.056	0.907

Kernel matching					
Time span	Treated	Controls	ATT	Std.Err.	t-stat
t+1/t	165	615	0.036	0.033	1.096
t+2/t	165	615	0.067*	0.035	1.900
t+3/t	165	615	0.018	0.051	0.354

Source: SORS, Slovenian Customs Office and own calculations.
Notes: Standard errros for kernel matching are based on bootstraping.
*, **, *** indicate statistical significance at 10, 5 and 1 per cent, respectively.

confirm our findings based on innovation survey that exporting decision does not trigger significant increases in product innovation.

Table 13: Treatment Effects for Total Factor Productivity

Nearest neighbor matching					
Time span	Treated	Controls	ATT	Std.Err.	t-stat
t+1/t	165	131	0.140***	0.042	3.352
t+2/t	165	130	0.156***	0.070	2.220
t+3/t	165	132	0.239***	0.067	3.562

Kernel matching					
Time span	Treated	Controls	ATT	Std.Err.	t-stat
t+1/t	165	615	0.110***	0.035	3.145
t+2/t	165	615	0.097*	0.060	1.625
t+3/t	165	615	0.168***	0.046	3.670

Source: SORS, Slovenian Customs Office and own calculations.
Notes: Standard errros for kernel matching are based on bootstraping.
*, **, *** indicate statistical significance at 10, 5 and 1 per cent, respectively.

Similarly, Table 13 reports results for the impact of exporting on process innovations. Estimates of ATT for the change of TFP over first three years after starting exporting demonstrate large and statistically significant effects of exporting decision on firm productivity for a set of small and medium sized firms. Based on nearest neighbor matching, we find that one year after the start of exporting, the average productivity of firms increases by 14 percentage point faster in comparison to non-exporters. In subsequent periods, the

effect further increases.[21] The results based on kernel matching are lower, but also statistically significant, which leads us to conclude that exporting does lead to productivity improvements that are likely to be related to process rather than product innovations.
These results are in line with the previous subsection, where exporting is shown to increase the probability of medium and large sized first time exporters to become future process innovators. The results are striking since both the likelihood of engaging in process innovators after starting exporting (using the innovation survey) as well as the likelihood of increasing the TFP after starting exporting (using the industrial production survey) are obtained on a very similar sample of medium and large sized first time exporters. One can therefore conclude that for Slovenian firms exporting leads to process rather than product innovations which in turn boost productivity. This causal relationship, however, is not general but is likely to be limited to a group of medium and large sized first time exporters only.

6 Conclusions

In this paper we explore the causal relationship between innovation and exporting activities of firms. The majority of papers study only correlation between these two activities, while we disentangle the causal link between the two. We argue that two causal links can be identified. First, the *product innovation - productivity - decision to export* link may effectively explain how firm's decision to invest into R&D and to innovate a product drives its productivity and triggers the decision to start exporting. And, second, the *exporting - process innovation - productivity growth* causal link may provide a missing link in understanding how exporting activity may have forced a firm to undergo process innovation, which in turn improves its productivity growth in the long run. Our empirical approach is tackling both sides of the causality link by using the Slovenian microdata, including financial data, innovation survey data, industrial survey data as well as the information on trade flows, for the period 1996-2002. This unique dataset allows us to test the prediction that firm's innovation enhances its probability of becoming an exporter as well as the prediction that learning effects of exporting will manifest themselves in greater effort to innovate and thus improve its productivity.
In the first step, we aim at merely establishing the correlation between innovation activity and exporting by applying bivariate probit regressions of the model of simultaneous exporting and innovation equations. These results show that past innovation does not increase likelihood of exporting, whereas past exporting does have a positive impact on innovation. These results are confirmed when we apply matching techniques. We also

[21] Note that these results on learning-by-exporting for Slovenian firms are more pronounced compared to the evidence reported by Damijan and Kostevc (2006) and De Loecker (2007) for the entire sample of new exporters.

check for the direction of causality between both variables by testing whether lagged innovations have an impact on decision to start exporting and whether past exporting affects firms decision to start innovating. We estimate average treatment effects on probabilities of exporting and innovating using innovation survey data as well as industrial production survey data.

We find no evidence that either product or process innovations increases the likelihood of becoming a first time exporter. However, we find evidence tht past exporting status increases the probability of medium and large sized firms to become process innovators. At the same time we find no impact of past exporting on product innovations. These results are reinforced with estimated treatment effects when using the industrial production survey data. We find no impact of past exporting on the number of products that firms produce, which is a direct evidence that exporting firms are not faster product innovators. However, we do find a positive impact of past exporting on productivity growth of medium and large first time exporters, which is an indirect evidence of process innovations.

These findings suggest that participation in trade may improve efficiency of firms through process innovations. One should note, however, that these positive effects are likely to be limited to a group of medium and large sized first time exporters. Export volumes of small first time exporters are probably too small to achieve immediate efficiency gains through process innovations. Alternatively, longer time span of data is needed in order to observe improvement of efficiency also in small firms.

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Appendix

Table A1: Industry average treatment effects of lagged export status (lagged innovation) on current innovation (current export status

industry	export equation			innovation equation		
NACE 2-digit	ATT	SE[a]	obs.[b]	ATT	SE[a]	obs.[b]
15	0.004	0.253	101 (150)	−0.207	0.246	284 (191)
17	0.085***	0.020	51 (99)	0.511***	0.099	253 (29)
18	−0.065	0.174	16 (124)	0.267***	0.106	197 (35)
19	0.124***	0.051	11 (39)	0.630***	0.204	79 (10)
20	0.149*	0.098	30 (144)	−0.212*	0.121	267 (43)
21	0.088**	0.038	12 (54)			
22	−0.023	0.290	12 (126)	−0.252	0.298	177 (60)
24	−0.002	0.044	68 (55)	0.637***	0.109	231 (9)
25	0.095***	0.019	41 (102)			
26	−0.056	0.163	33 (106)	0.502**	0.220	240 (45)
27	0.142***	0.037	22 (44)			
28	0.082***	0.014	81 (268)	0.361***	0.068	571 (93)
29	0.057	0.115	124 (160)	0.575***	0.208	509 (40)
30	0.447	0.352	8 (21)	0.250	0.361	26 (18)
31	0.141***	0.030	56 (53)			
32	0.079*	0.042	44 (25)	0.616***	0.118	128 (12)
33	0.798***	0.302	38 (53)	0.589***	0.130	158 (20)
34	0.094***	0.026	29 (51)			
36	0.079***	0.022	42 (145)	0.394***	0.101	313 (50)
37	0.051	0.042	3 (14)			

Notes: [a] bootstrapped standard errors (100 repetitions)

[b] number of treatment observations, number of control observations in parentheses.

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

Table 14: Exporting decision: Propensity score estimation

Variable	Coefficient (Std. Err.)
log(TFP) in t-1	-0.188
	(0.081)**
log(capital per employee) in t-1	0.081
	(0.035)**
log(employment) in t-1	0.173
	(0.048)***
log(number of products) in t-1	0.042
	(0.06)

Source: SORS, Slovenian Customs Office and own calculations.

Notes: *,**,*** denote statistical significance at 5, 1 and 0.1 percent.